Automatic Continuous Commissioning of Measurement Instruments in Air Handling Units

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Abstract: This paper presents a robust strategy based on a condition-based adaptive statistical method for automatic commissioning of measurement instruments typically employed in air-handling units (AHU). The multivariate statistic method, principal component analysis (PCA), is adopted and modified to monitor the air handling process. Two PCA models are built corresponding to the heat balance and pressure-flow balance of the air-handling process. Sensor faults can be detected and isolated using the Q-statistic and the Q-contribution plot. The fault isolation ability against typical component faults is improved using knowledge-based analysis. A novel condition-based adaptive scheme is developed to update the PCA models with the operation conditions for continuous online application. A commissioning tool is developed to implement the strategy. Simulation tests and field tests in a building in Hong Kong were conducted to validate the automatic commissioning strategy for typical AHU. The integration of the tool with a building management system (BMS) and its application is demonstrated.

Keywords: continuous commissioning, sensor, fault detection and diagnosis, air-handling unit, principal component analysis

1. INTRODUCTION

Due to the growing complexities and scales of modern buildings and their associated heating, ventilation and air-conditioning (HVAC) systems as well as the increasing demands of the society on building energy and environment performance, the need for automatic continuous commissioning of HVAC systems is greater than ever before. Commissioning has traditionally been viewed as a task performed after system assembly and before hand-over to check operational performance as a final checkout and acceptance test. Nowadays, a broader view is widely accepted in the construction industry in North America and Europe [1-3]. As a quality-oriented process for verifying the performance of building systems to meet intended objectives and criteria, commissioning has been recognized as a valid means to improve energy performance of buildings and HVAC systems by International Energy Agency (IEA) and widely studied in the research projects of Annex 40[2] and Annex 47[3]. An open publication [4] found a media payback period of 4.8 years for commissioning of new buildings in United States. Additionally, commissioning ought to be a process rather than a task, which should be conducted continuously because HVAC systems easily suffer from various faults due to abnormal physical changes, aging and etc. Such faults may go unnoticed for extended periods of time. Continuous commissioning can promptly find the faults and rectify them, and consequently improve system performance. It was found median cost saving on energy of 15% and payback periods of 0.7 year for periodical commissioning of existing building [4].

Research and development (R&D) on automatic commissioning of building systems are active in recent years [5,6]. Many automatic commissioning techniques and tools have been emerging from the R&D efforts, and the automatic fault detection and diagnosis (FDD) of the heating, ventilation and air-conditioning (HVAC) systems are a popular focus [7-10]. However, commissioning outcome is largely dependent on the measurement quality. Measurement instruments may suffer from aging, deterioration, complete failure and etc. Therefore, automatic continuously commissioning of measurement instruments is necessary for reliable monitoring and control as well as automatic commissioning of building systems.

This paper summarizes the outcome of a research project on AHU sensor FDD. It presents a robust strategy for automatic continuous commissioning of typical measurement instruments in typical air-handling units including temperature sensors of the fresh air, return air and supply air, flow rate sensors of the fresh air, return air and supply air, humidity sensors of the return air and fresh air, and the static pressure sensor of the supply air. An automatic commissioning tool is also developed to implement the strategy in BMS in this research.

2. OVERVIEW OF COMMISSIONING STRATEGY

Fig. 1 shows the structure of the robust commissioning strategy that includes an isolation-enhanced sensor FDD scheme (the dash surrounded part at the right) and the condition-based adaptive scheme (at the left of the figure). Two PCA models are built using data under normal operating conditions of the air handling process. The Q-statistics (outputs of PCA models) is used to as a fault index. Sensor faults are diagnosed using an isolation-enhanced PCA method that combines the Q-contribution plot and knowledge-based analysis. A condition-based adaptive scheme is employed to update the PCA models to follow the normal shifts in the process. A PCA model database is built, which stores the PCA models generated in the adaptive process. These models can be used to monitor the air-handling process under similar operating conditions in the future application. Each part of the robust sensor commissioning strategy is briefly introduced in the following sections.

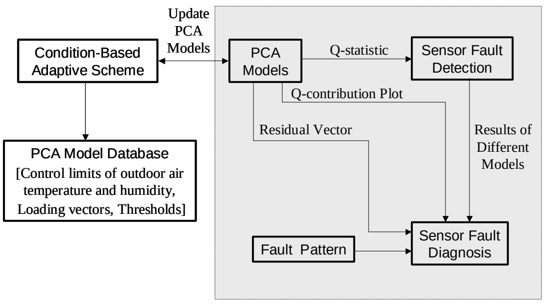


Fig. 1 Structure of the diagnostic strategy

3. OUTLINE OF PCA METHOD IN FDD APPLICATION

PCA [11, 12] is a popular multivariate statistical analysis method. Variables in a modern engineering process are usually multi-dimensional and correlated. The correlations among process variables can be represented by a smaller number of variables because of the redundancy of the process variables.

Measurement space (X), constructed by measurements of correlated process variables, can be decomposed into two orthogonal subspaces using the PCA method, i.e. the residual subspace (E) and the principle component (PC) subspace ($\hat{X}$) as shown in Eq. (1). X can be mathematically defined using a matrix of the order of n rows (samples) and m columns (process variables).

$$X = \hat{X} + E \qquad (\hat{X} \perp E) \qquad (1)$$

The PC subspace contains the major normal variations of the correlations. The direction of the PC subspace is defined by the loading vectors (P), which are parts of the eigenvectors of the covariance matrix (Cov) of X. In practice, Cov is usually estimated from samples of variables under normal condition, as shown in Eq. (2).

$$Cov = X^T X \Big/ (n-1) \qquad (2)$$

Usually, Cov has m eigenvectors. In the application of PCA, only those eigenvectors, P ($P \in \Re^{m \times k}$, $k<m$), which are associated with the first k largest eigenvalues, are retained in the PCA models, because they represent the direction of most variance of a process. Therefore, the original m-dimensional measurement space can be represented by the k-dimensional PC subspace. Edward (1991) suggested about ten commonly used criteria.

While a new sample ($x_{new} \in R^m$) is monitored, it can be decomposed into two parts as shown in Eq. (3). $\hat{x}_{new}$ is the projection on the PC subspace containing the main variations of the process correlations, and e is the projection on the residual subspace known as residual vector.

$$x_{new} = \hat{x}_{new} + e \qquad (3)$$

The projection matrix (C_x) is calculated using Eq. (4), given that the loading vectors P are orthonormal. $\hat{x}_{new}$ is calculated using Eq. (5), and the residual vector, i.e. $e \in R^m$ is calculated using Eq. (6).

$$C_x = P(P^T P)^{-1} P^T = PP^T \qquad (4)$$

$$\hat{x}_{new} = C_x x_{new} = PP^T x_{new} \qquad (5)$$

$$e = x_{new} - \hat{x}_{new} = (I - PP^T) x_{new} \qquad (6)$$

In FDD applications, the squared sum of the residual, namely the Q-statistic calculated using Eq. (7), is used as an index for fault detection.

$$Qstatistic = \|e\|^2 = \|(I - PP^T) x_{new}\|^2 \le Q_\alpha \qquad (7)$$

where Q_α denotes a statistical threshold for the Q-statistic [11]. When no fault exits, the Q-statistic less than Q_α represents the normal dynamics and measurement noises, etc. of the process. When a fault occurs, a higher value of the Q-statistic is detected. Once a fault is detected using the Q-statistic, the Q-contribution plot can be used to diagnose the fault. The contribution of the individual variables to the Q-statistic is compared, and the variable making the largest contribution to the Q-statistic is most relevant to the fault.

4. ISOLATION-ENHANCED PCA METHOD

From above introduction, it can be found that no inner knowledge about the process or system monitored is required by the PCA method. The advantage of such a non-physical and data-driven nature is avoiding difficulties in setting up models and rules as well as identifying parameters. However, the disadvantage is weak in finding the real fault source as variables are correlated and fault may propagate in the process. Therefore, it is necessary to improve the fault isolation ability of the PCA method.

The basic idea to improve the fault isolation ability of the PCA-based FDD method in this study is to explore and make use of new physical information besides the Q-statistics and Q-contributions. It was found that the residual vectors, e in Eq. (6), can reflect some faulty symptoms which can be interpreted physically. The elements (e_i) represent the unmodeled variations of corresponding variables. The residual vector indicates the discrepancy of the new samples to its statistical expectation. The elements of the residual vector have two possible signs, positive and negative, which represent two changing directions, increase and decrease. Under normal conditions, the elements of e fluctuate around zero, but their squared sum, i.e. the Q-statistic, is under its statistical threshold with certain confidence level. The elements of e are seldom equal to zero due to process dynamics, measurement noises and other disturbances. If the measurement of the *ith* variable is larger than its statistical expectation, the *ith* element of the residual vector e is positive, and vice versa. By interpreting signs of the residual vector *e*, the changing directions of measured variables can be determined, which can be used as fault symptoms.

On the other hand, although the changing magnitudes of the variables affected by a sensor fault are always difficult to be quantified in practice, the changing directions of the affected variables, namely fault patterns in this study, are certain and can be deduced from process characteristics. By comparing the fault symptoms reflected by the residual vectors and the fault patterns, the sensor faults can be isolated. The unique fault patterns of typical sensor faults in typical AHU will be identified using knowledge-based analysis in the following section.

5. APPLICATION OF PCA METHOD IN COMMISSIONING AHU SENSORS

The PCA method has been successfully applied to detection and diagnosis of sensor faults [10, 13] in a typical AHU as shown in Fig. 2.

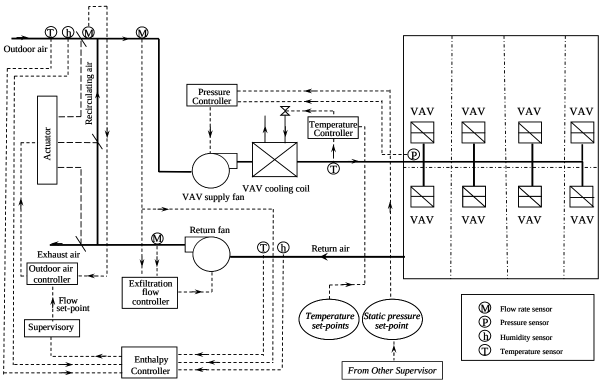


Fig. 2 Schematic of AHU and measurement instruments

Two PCA models, the heat balance model and the pressure-flow balance model are built to make variables in individual model more closely correlated. Some control signals are also involved in the PCA models to make correlations closer. The PCA model based on the heat balance involved nine variables: M_{fre}, M_{sup}, M_{rtn}, T_{fre}, T_{sup}, T_{rtn}, h_{fre}, h_{rtn}, and $C_{w,val}$, which constructed a nine-dimensional measurement space. The PCA model based on the pressure-flow balance of the process involved six measured variables: M_{fre}, M_{sup}, M_{rtn}, P_{sup}, C_{fans} and C_{fanr}, where C_{fans} and C_{fanr} were the supply and return fan control signals respectively, which constructed a six-dimensional measurement space. All these measurements are typically available in BMSs. The two PCA models are trained using samples of under normal operation conditions. The residual vectors obtained from the PCA models are shown as Eq. (8)-(9).

$$e_A = \begin{bmatrix} e_{Mfre} & e_{M\sup} & e_{Mrtn} & e_{Tfre} & e_{T\sup} & e_{Trtn} & e_{hfre} & e_{hrtn} & e_{w,val} \end{bmatrix}^T \quad (8)$$

$$e_B = \begin{bmatrix} e_{Mfre} & e_{M\sup} & e_{Mrtn} & e_{P\sup} & e_{fans} & e_{fanr} \end{bmatrix}^T \quad (9)$$

Tab. 1 Fault Patterns Describing Cause-Effect Relations in the Heat Balance Model

Fault \ Fault Pattern	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9
T_{sup} (+)	x	x	x	x	+	x	x	-	+
T_{sup} (-)	x	x	x	x	-	x	x	+	-
h_{rtn} (+)	x	x	x	x	-	x	x	+	+
h_{rtn} (-)	x	x	x	x	+	x	x	-	-

Tab. 2 Fault Patterns Describing Cause-Effect Relations in the Pressure-Flow Balance Model

Fault \ Fault Pattern	e_1	e_2	e_3	e_4	e_5	e_6
M_{sup} (+)	x	+	+	-	-	+
M_{sup} (-)	x	-	-	+	+	-
M_{rtn} (+)	x	+	+	+	+	-
M_{rtn} (-)	x	-	-	-	-	+
P_{sup} (+)	x	-	-	+	-	-
P_{sup} (-)	x	+	+	-	+	+

('X' means uncertain, '+' means positive bias, '-' means negative bias.)

Knowledge about the process is used to identify fault patterns. Fault patterns describing cause-effect relations between variables are shown in Tables 1 and 2. These fault patterns describe multiple couples (rows) of sensor faults and their correspondent symptoms, which can easily be understood by checking the physical characteristics of the air-handling process. Each couple is defined by the fault direction (negative or positive biases) of a faulty sensor and the changing direction (increasing or decreasing magnitudes) of the measurements of the affected variables.

Because the fault patterns in Table 1 and 2 are unique, the robustness of the fault diagnosis method against the process and component faults is enhanced.

6. CONDITION-BASED ADAPTIVE SCHEME

The main weakness of the PCA-based FDD method is that PCA models, once built from the training data, are time-invariant, while air-handling processes are always time-variant [14]. It is inappropriate to use a time-invariant model to monitor a time-varying process. The reliability of the PCA-based FDD method in long-term continuous online applications may be significantly affected.

In this study, the PCA models were updated using a novel adaptive scheme, namely the condition-based adaptive method. The adaptive scheme updates PCA models with changing operating conditions and stores the PCA models generated in the adaptive process in a model database. The condition-based adaptive scheme is more computational efficient than the conventional time-based adaptive scheme. At the same time, it also improves the performance of the adaptive PCA method in detecting slowly developing faults.

How to Update

Matrix $X_t \in R^{n\times m}$ (n samples of m variables) contains the training data of a PCA model at time t. A moving window is moving between historical samples and new samples. New samples ($x_{t+1} \in R^{n_1\times m}$, n_1 samples of m variables) at time $t+1$, which have been detected to be normal, will be used to force out the same number of the oldest samples ($X_t^{(1)}$) in the training matrix. Therefore, the training matrix at time $t+1$ becomes $X_{t+1} = \begin{bmatrix} X_t^{(2)} \\ x_{t+1} \end{bmatrix}_{(n_2+n_1)}$, where $n = n_1 + n_2$ is the size of the moving window. The updated training matrix is used to build the new PCA model. Because the newest normal samples continuously replace the oldest ones, the training matrix always contains the most recent operating data, and the PCA model deduced from the training matrix can follow the normal shifts in the process.

When to Update

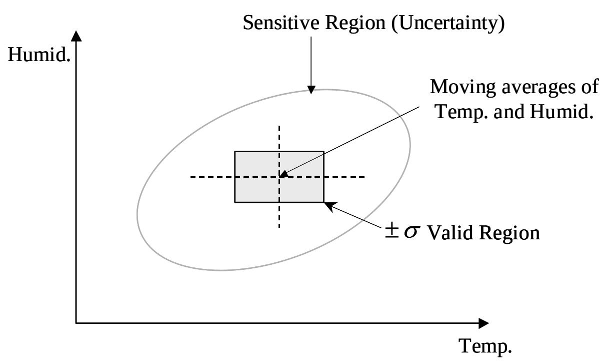


Fig. 3 Schematic of the valid region for monitoring outdoor climate

Since the variances of the indoor conditions including occupants, equipment loads and etc, are easily represented using one PCA model, the PCA models are to be updated with the changes of the outdoor climate. The outdoor air temperature and humidity are selected for monitoring the outdoor climate and for determining the time for updating the PCA models. Since the training matrixes are scaled to zero mean and unit variance to remove the influence of units of different variables, the limits with $\pm\sigma$ (σ represent the standard variances in the outdoor air temperature and humidity) are selected to monitor the outdoor air temperature and humidity. The region surrounded by the $\pm\sigma$ limits is called the valid region of the heat balance PCA model, as shown in Fig. 3. The center of the valid region is the intersection of the averages of the outdoor air temperature and humidity in the training matrix. The intersection moves when new samples force out old samples in the training matrix. While the intersection moving out of the valid region, the PCA models are updated. The PCA models generated during the adaptive process will be saved in a database, the so-called PCA model database.

7. IMPLEMENTATION OF ROBUST COMMISSIONING STRATEGY

A commissioning tool implementing the robust strategy is developed and integrated with a real BMS via an intelligent building management platform

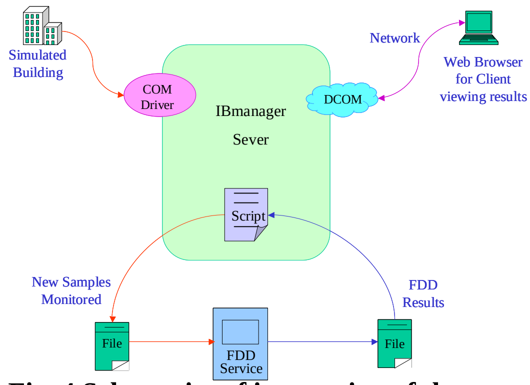


Fig. 4 Schematics of integration of the commissioning tool with the BMS

namely IBmanager [15]. The IBmanager is an open IB systems integration and management platform based on middleware technologies developed in our Intelligent Building Laboratory. The virtual building simulating the building and HVAC system using a building emulator [16] is linked to a real BMS, to study operational performance of the commissioning tool. Fig. 4 shows the schematics of integration of the commissioning tool with IBmanager.

8. VALIDATION AND APPLICATION DEMOSTRATION

Both simulation tests and tests using sitedata from an existing building in Hong Kong were conducted. The simulator was built using the models developed by Wang [16], which simulate a typical air-handling unit working in a variable air volume (VAV) air-conditioning system. In this paper, examples of test results are presented to illustrate the performance of the robust strategy.

Fixed biases were introduced to each sensor in the simulated air-handling process. Only one sensor was biased in each simulation test. Figure 5 and Fig. 6 show that the PCA models successfully detected all sensor faults. Fig.7 shows the fault symptoms represented by the residual vectors of the pressure-flow balance PCA model when the supply air flow rate sensor was biased with negative and positive values respectively. The fault symptoms match the fault patterns shown in Table 2.

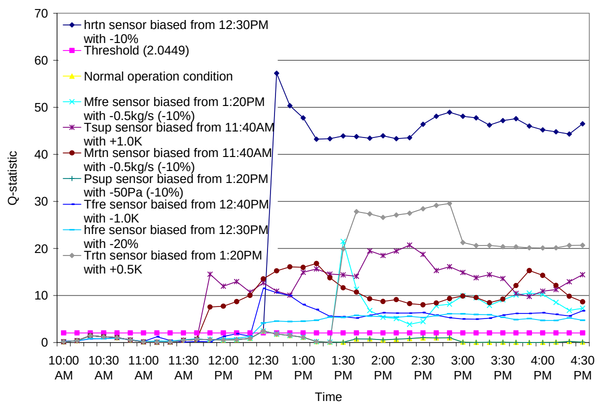


Fig. 5 Q-statistic plot of simulation tests (heat balance PCA model)

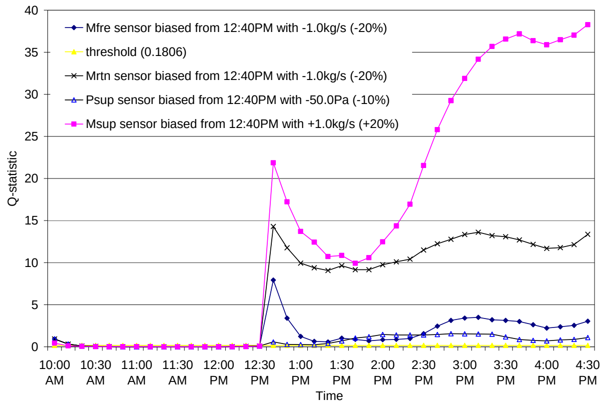
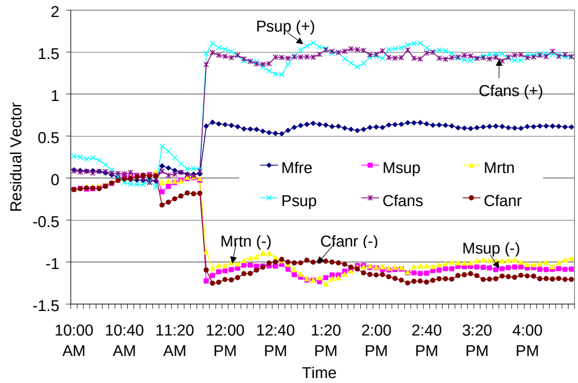


Fig. 6 Q-statistic plot of simulation tests (pressure-flow balance PCA model)

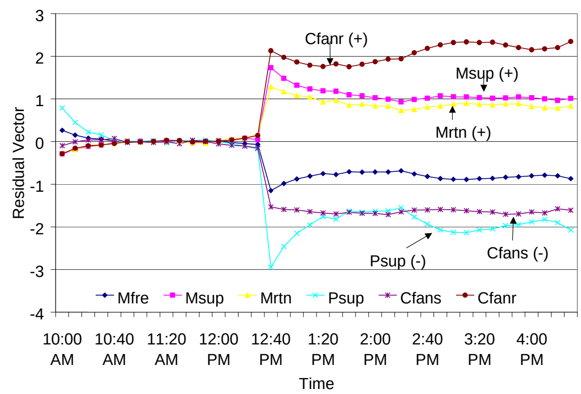
In order to validate the update of the PCA models in long term, normal data in eight days were retrieved from the BMS of an existing building in Hong Kong. The eight days were selected from four months (i.e. April, May, June and July in 2002 respectively,) and two days were selected in each month. Normal data in one more day in the April was selected as the training data. Sensor commissioning records showed that the AHU operated under normal conditions during those days. All data were sampled at the intervals of 2 minutes.

Fig. 8 shows the monitoring results without updating the PCA model. It can be found that the initiate PCA model failed in monitoring the real AHU sensors, because the Q-statistics of most samples exceed the threshold even though these samples are normal according to the commissioning record. Then, the robust strategy using the condition-based adaptive PCA method was used to monitor the real AHU sensors. Fig. 9 shows the monitoring results. The monitoring result is much better than that of the basic scheme. The test validates that the condition-based adaptive PCA method can make the PCA model follow the normal shift of the air-handling process.

Fig. 10 shows the interface of the commissioning tool in the web page format in the Microsoft Internet Explorer window.



a. Msup sensor biased with –0.5kg/s from11:45AM



b. Msup sensor biased with +1.0kg/s from12:40PM

Figure 7 Test results under the supply air flow rate sensor faults - the pressure-flow balance PCA model

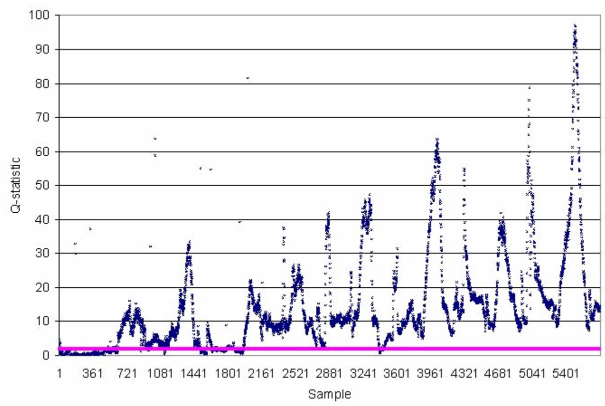


Fig. 8 Q-statistic plot of monitoring AHU sensors in a real building under normal sensor conditions without updating the PCA model

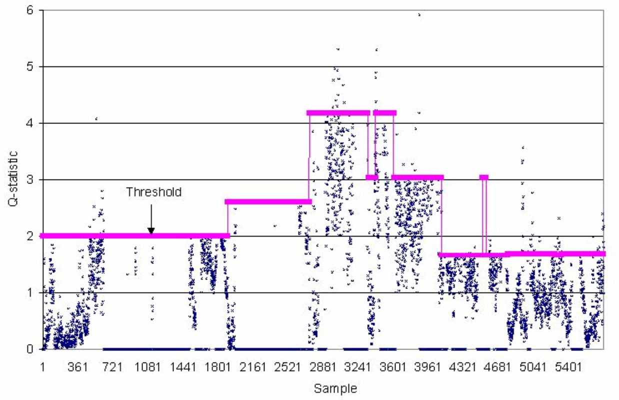


Fig. 9 Q-statistic plot of monitoring AHU sensors in a real building under normal condition using the robust strategy

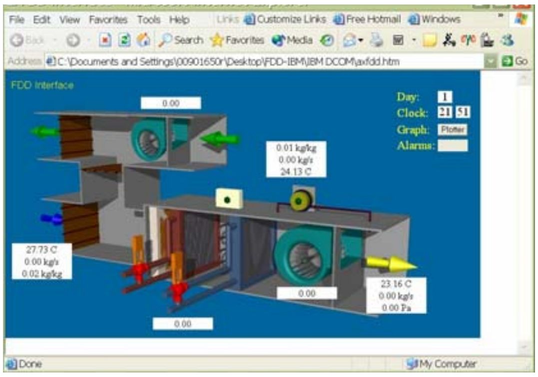


Fig. 10 Interface of the commissioning tool

9. CONCLUSION

Automatic continuous commissioning of measurement instruments is necessary to reliable monitoring, control and commissioning of HVAC systems. This paper summarizes the outcomes of a research project on sensor FDD in typical AHUs. A robust strategy and tool for automatic continuous commissioning of AHU sensors is presented. Both simulation tests and tests using sitedata from an existing building validated the high effectiveness and robustness of the commissioning strategy.

The PCA method was modified in this study to improve its sensitivity, detectability, and fault isolation ability for automatic continuous online application. By planting physical knowledge about the air-handling process into the purely data-driven PCA method, the PCA-based FDD method became more effective and reliable in diagnosing sensor faults while allowing the PCA model outputs to be more meaningful and understandable. The robustness of the sensor fault isolation approach is also improved because the fault pattern and fault symptom of a particular sensor fault are unique. The condition-based adaptive scheme developed in this study allows the PCA-based FDD to follow normal shifts of the air handing process. The condition-based adaptive scheme also overcomes the shortcomings of the time-based adaptive scheme as it reduces the risk of the PCA models adapting to slowly developing faults. At the same time, the frequency with which the PCA models are updated also decreases, and consequently the condition-based adaptive scheme is more computationally efficient and more suitable for online applications.

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NOMENCLATURE

X Variable matrix under normal operating conditions ($X \in R^{n \times m}$), *n* samples of *m* variables
E Residual space
Cov Covariance matrix of *X*
x Vectors of variables ($x \in \Re^m$)
e Residual
P Loading vectors of PC
Q_α Threshold of Q-statistic
T Temperature (°*C*)
M Flow rate (*kg/s*)
h Humidity (*kg/kg*)
P Pressure (*Pa*)
C Control signal
A Training matrix of the heat balance PCA model
B Training matrix of the pressure-flow balance PCA model
R Covariance matrix
σ Standard variance

Superscripts and Subscripts
^ Estimated value
T Transpose matrix
new New samples
sup Supply air
fre Fresh air
w Chilled water
fanr Return air fan
val Valve
rtn Return air
exh Exhaust air
fans Supply air fan
coil Cooling coil

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